STUDY ON VEHICLE ROUTING OPTIMIZATION OF COLD CHAIN LOGISTICS WITH SOFT TIME WINDOW UNDER STOCHASTIC DEMAND

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In the paper, a vehicle routing opportunity constrained model is proposed. The objective function of the model is to minimize the total cost including fixed cost, transportation cost, refrigeration cost, damage cost, penalty cost and shortage cost. According to the characteristics of the model, an algorithm combining Monte Carlo with Periodic Evolutionary Genetic Algorithm is designed to solve the model. Through practical application case, the convergence of the algorithm is illustrated, and the influences of the change of customer satisfaction rate and customer demand maximum deviation on the total cost are analyzed. The results show that the model and algorithm can effectively and feasibly solve the routing problem of stochastic demand in cold chain distribution system. It can provide scientific decision-making reference for the distribution of cold chain logistics enterprises.

Keyword: Cold chain logistics; Vehicle routing; Periodic Evolutionary Genetic Algorithm; Monte Carlo

1. Introduction

In recent years, with the continuous improvement of people’s living standard in China. Consumers put forward higher requirements for food safety, freshness and convenience, as well as diversity of food categories. The food is not limited in original production and consumption field, which promotes the rapid development of the cold chain logistics industry. Cold chain logistics means that frozen foods, special logistics to ensure food quality, is always in a prescribed low temperature environment in the production, storage, transportation, sales and other links [1]. The particularity of cold chain logistics is mainly due to the perishable of the products and the high requirement of timeliness. The value of the products will gradually decrease with the passage of time, which increases the cost of distribution. This requires the distribution enterprises to formulate reasonable distribution routes, improving the efficiency of distribution.

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Vehicle Routing Problem (VRP) is a vital problem and a crucial link in reducing the total cost of distribution of cold chain logistics. VRP and its variants have been studied in many previous works. The vehicle routing problem of cold chain logistics were studied by literature [2-12]. Literature [13-19] studied the normal temperature logistics under stochastic demand. For example, Osvald et al. [2] studied vehicle routing problem with time windows, time dependent and travel-times (VRPTWTD). A tabu search optimization algorithm was designed to solve the model. A non-linear mathematical model was established to maximize the expected total profit of suppliers by Chen [3], and the model can determine the optimal production quantity, start-up time and vehicle routing simultaneously. Belo-Filho et al. [7] studied the supply chain planning of products with limited life span, and an adaptive large neighborhood search framework was proposed to solve the problem. Amorim et al. [8] taking Portugal food distribution company as an example. Adaptive large neighborhood search framework was used to optimize the distribution routing, and the optimized paths were compared with the company’s plan, which proves the advantages of the algorithm. Song et al. [9] developed a nonlinear mathematical model with the objective of maximizing the total level of the customer satisfaction. The validity of the model was proved by numerical examples. Ma et al. [10] studied the vehicle routing optimization model of cold chain logistics with mixing windows based on stochastic demand. Zhao [14] established multi-objective vehicle routing model under random demand with soft time window. The stochastic demand was processed by preoptimization strategy, and a hybrid particle swarm optimization algorithm based on Pareto was designed to solve the model. A multi-objective mathematical programming model based on fuzzy satisfaction degree was established, and quantum evolutionary algorithm and the piecewise optimization method of particle swarm optimization were used to solve the Pareto solution by Zhao [15]. Marinaki et al. [16] proposed a new hybrid algorithm. The algorithm combination neighborhood topology glowworm swarm optimization with variable neighborhood search algorithm. The effectiveness of the algorithm was proved by the two test examples. Andres et al. [17] a hybrid meta-heuristic algorithm was designed to solve the vehicle routing problem with stochastic demand, and the test results of 40 benchmark examples showed that the method was superior to the existing metaheuristic algorithm in quality and efficiency. Salavati-Khoshghalb et al. [18] proposed a more advanced rule-based recourse policy, which does not solely depend on the vehicle’s residual capacity. Zhang et al. [19] proposed three probabilistic models for on-time delivery from different perspectives, and Numerical examples are given to illustrate the applicability of the three models.

It is well known that the research results of VRP in cold chain logistics considering customer stochastic demand are relatively few, and the cold chain logistics distribution routing was mainly based on the normal temperature
logistics distribution routing problem. Therefore, the cost function of cold chain logistics distribution routing was not comprehensive enough, and when it comes to the transformation of customer stochastic demand constraint conditions. Many studies assume that customer demand probability distribution was normal distribution, but in fact not all the statistical attributes of the customer’s needs satisfy the central limit theorem [20]. In view of this, this paper establishes a mathematical model of cold chain logistics distribution VRP with the objective function of minimum comprehensive cost, and the satisfaction rate of customer requirements is introduced into the constraint conditions. Under the assumption that the probability distribution of customer demand is unknown, and customer demand is evaluated in a random interval. Monte Carlo simulation method is introduced into the Periodic Evolutionary Genetic Algorithm, to deal with the opportunity constraint (8).

The remainder of this paper is organized as follows: the description of the problem and a mathematical model are presented in Section 2; the proposed algorithm is introduced in Section 3; a numerical example and concluding remarks are discussed in Section 4 and 5, respectively.

2. Model Formulation

2.1 Problem description

The problem can be described as follows. Within a given area, a cold chain logistics distribution center provides cold chain products distribution services for multiple customers. Distribution center and customer’s geographical location are known, but customer’s demand is unknown. Different customers have different requirements for the delivery time of goods. This paper studies how to reasonably arrange the distribution routes of refrigerated vehicles to make the goods arrive within the time acceptable to the customers. Minimize the total distribution cost when the customer’s demand and vehicles capacity are satisfied.

2.2 Parameters and variables

To build the model, Parameters and variables can be shown in Table 1.

<table>
<thead>
<tr>
<th>Parameters and Variables</th>
<th>Meaning</th>
</tr>
</thead>
<tbody>
<tr>
<td>$M$</td>
<td>The number of customers</td>
</tr>
<tr>
<td>$K$</td>
<td>The number of refrigeration vehicle owned by the distribution center</td>
</tr>
<tr>
<td>$Q$</td>
<td>Maximum load of refrigerated vehicle</td>
</tr>
<tr>
<td>$d_{ij}$</td>
<td>The distance between customer $i$ and customer $j$</td>
</tr>
<tr>
<td>$t_{ik}$</td>
<td>The time when the refrigerated vehicle $k$ arrives at the $i$ customer</td>
</tr>
<tr>
<td>$t_{ijk}$</td>
<td>The driving time of refrigerated vehicle $k$ between customer point $i$ and customer point $j$</td>
</tr>
</tbody>
</table>
The service time required by customer \( j \)  

The fixed cost of refrigerated vehicle \( k \)  

Remaining cargo volume when refrigerated vehicle reaches the customer \( j \)  

Remaining cargo volume when refrigerated vehicle leaves the customer \( j \)  

Average speed of refrigerated vehicles  

The actual load of refrigeration vehicle \( k \)  

The demand of customer \( i \)  

The refrigeration cost which generate during transportation process of unit time  

The refrigeration cost which generate during unloading process of unit time  

Price of unit commodity  

The spoilage rate which generate during transportation process of unit time  

The spoilage rate which generate during unloading process of unit time  

The time window that the customer \( i \) expects to be served  

The time service window that the customer \( i \) can be accept  

Out of stock cost per unit cold chain product  

The actual total demand for customer points served by refrigerated vehicle \( k \)  

Customer demand satisfaction rate.  

\( x_{ijk} \) = 1 represents the refrigeration vehicle \( k \) passes the section between customer \( i \) and \( j \), otherwise \( x_{ijk} = 0 \)  

\( x_{jk} \) = 1 represents refrigerated vehicle \( k \) provides service for customer \( j \), otherwise \( x_{jk} = 0 \)  

\( Y_k \) = 1 represents refrigerated vehicle \( k \) of distribution center is used, otherwise \( Y_k = 0 \)  

### 2.3 Model formulation

The stochastic demand vehicle routing model of cold chain logistics with minimum total cost as objective function is established as shown follows:

\[
\min z = \sum_{k=1}^{K} f_k Y_k + \sum_{k=1}^{K} \sum_{i=0}^{M} \sum_{j=0}^{M} c_{ij} x_{ijk} d_{ij} + P(\sum_{k=1}^{K} \sum_{i=0}^{M} \sum_{j=0}^{M} d_{ij} x_{ijk} u_j) + \sum_{k=1}^{K} \sum_{i=0}^{M} x_{ijk} \left(t_{ijk} + \max\{ET_i - t_{ik}, 0\}\right) + B_2 \sum_{k=1}^{K} \sum_{j=0}^{M} x_{jk} s_j + \sum_{k=1}^{K} \sum_{i=0}^{M} \max\{N_k - S_k, 0\} + \sum_{k=1}^{K} \sum_{i=0}^{M} \left(\theta_3 \max\{ET_i - t_{ik}, 0\} + \theta_4 \max\{t_{ik} - LT_i, 0\}\right)
\]  

(1)
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Subject to

$$\sum_{k=1}^{K} \sum_{j=0}^{M} x_{jk} \leq K$$  \hspace{1cm} (2)

$$\sum_{i=0}^{M} x_{ijk} = x_{jik}, \ j = 0, 1, 2, \ldots, M; k = 1, 2, \ldots, K$$  \hspace{1cm} (3)

$$\sum_{j=0}^{M} x_{ijk} = x_{iik}, \ i = 0, 1, 2, \ldots, M; k = 1, 2, \ldots, K$$  \hspace{1cm} (4)

$$\sum_{k=1}^{K} x_{jk} = 1, \ j = 1, 2, \ldots, M$$  \hspace{1cm} (5)

$$t_{jk} = t_{ik} + t_{ai} + t_{ijk}$$  \hspace{1cm} (6)

$$S_k \leq Q \quad k = 1, 2, \ldots, K$$  \hspace{1cm} (7)

$$P(Y_k S_k \geq Y_k N_k) \geq \alpha \quad k = 1, 2, \ldots, K$$  \hspace{1cm} (8)

The objective function (1) contains fixed cost, transportation cost, damage cost, refrigeration cost, shortage cost, and penalty cost. In the case of satisfy the constraint conditions (2)-(8) minimize the total cost. Constraint (2) represents the existence of unused refrigerated vehicles in distribution center. Constraints (3) and (4) represent the flow conservation limits for each customer point. Constraints (5) indicate that each customer point is served only once by a refrigerated vehicle. Refrigerated vehicle maintain service continuity for two customer nodes which is imposed by constraint (6). The capacity limit of refrigerated vehicle is expressed by constraint (7). The satisfaction rate of customer demand is expressed by constraints (8).

3. Algorithm Design

An algorithm combining Periodic Evolutionary Genetic Algorithm with Monte Carlo is designed to solve the model in this paper. The algorithm simulates the phenomenon of “evolving-degeneration” in the process of natural evolution and presents the characteristic of periodic reciprocation reference [21-23]. The algorithm basic steps are shown as follows:

Step 1: Chromosomes coding. The number of vehicles dispatched, the number of customers served by per vehicle and the order of service are the primary decision variable for the model. Thus, the chromosomes are encoded by the corresponding arrangement coding method of vehicle and the customers, the basic idea is a customer permutation denoted by $M$ natural numbers do not repeat. Meanwhile a vehicle permutation expressed by $k$ natural numbers can be repeated ($k \in [1, K]$). These two permutations correspond to each other, and then a solution is formed. The solution is a distribution route scheme.

Step 2: Generate feasible initial population at random. Encoding the chromosomes produce the initial population according to the step 1 coding.
method. Monte Carlo simulation is used to verify whether the chance constraint \((8)\) is reasonable or not. Whether vehicle load and customers soft time window constraint is satisfied or not. The chromosomes can be preserved as a feasible solution if these conditions are satisfied, otherwise another chromosome will be produced until \(N\) feasible chromosomes are produced.

Step 3: Selection strategy. Calculate the fitness value of the individual, and the individuals are selected by roulette in the population.

Step 4: Crossover and mutation operation. Determine whether the evolution period is satisfied or not. Cycle crossover, insertion mutation, reversed mutation operations are performed on individual if the evolution period is satisfied. Otherwise, the cycle crossover and exchanged mutation operation are directly executed on individual. After obtaining the new generation individuals. Monte Carlo simulation is used to verify whether the chance constraint \((8)\) is reasonable or not. Whether vehicle load and customers soft time window constraint is satisfied or not, the path is redivided if the constrains condition are not satisfied. Otherwise step 5 is executed.

Step 5: Judge the termination condition. Iteration will stop if the maximum number of iterations is satisfied, and the best individual found in the process of solving is regarded as the final optimal solution. Otherwise, let \(gen = gen + 1\), go to step 3.

4. Description of Experimental Problems and Analysis of Experimental Result

4.1 Data description and parameters setting

Some of the data used are from reference [25], and we select 20 supermarkets as customers in the case. Suppose the customer’s demand probability distribution are unknown. The value range of customer \(i\) demand is \([q_i - \delta_i, q_i + \delta_i]\)(\(q_i - \delta_i \geq 0, \delta_i \geq 0\)), \(q_i\) and \(\delta_i\) are customer average demand and maximum deviation of customer demand fluctuation respectively. Based on historical data from the past years. The twenty customers average demand are 1.2, 0.5, 1.5, 1.5, 2, 2, 1.8, 2.5, 1.2, 1, 1.3, 1, 0.5, 1.5, 2.5, 1.5, 0.5, 2.5, 1.1 respectively. The coordinates, time window and service time of 20 customer points are shown in the table 2. The coordinate of distribution center is (35, 35). The refrigerated vehicles type are consistent with the maximum carrying weight of 9 tons in the delivery process. The model parameters are set as follows: \(v = 30\) km/h, \(c = 3\) Yuan/km. \(f_k = 200\) Yuan, \(B_1 = 15\) Yuan/h, \(B_2 = 20\) Yuan/h, \(P = 1000\) Yuan/t, \(\theta_1 = 0.002, \theta_2 = 0.003, \theta_3 = 60\) Yuan/h, \(\theta_4 = 60\) Yuan/h, \(\tau = 20\) Yuan/t.

The parameters setting for the algorithm have a considerable influence on the algorithm’s ability to solve the problem, thus affecting the results of the
model. We refer to the algorithm parameter setting in reference [26], and combined with the model established in this paper. The algorithm parameters are set as shown follows: the initial population $N$ is 100. The number of maximum generations is 500. The crossover probability $P_c$ and mutation probability $P_m$ are 0.7 and 0.1 respectively. 10 is set as the number of iterations of an evolution period.

Table 2

<table>
<thead>
<tr>
<th>Demand Point</th>
<th>X Coordinate (km)</th>
<th>Y Coordinate (km)</th>
<th>Prescribed time window</th>
<th>Acceptable time window</th>
<th>Service time (min)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>29</td>
<td>21</td>
<td>6:00-8:00</td>
<td>5:30-11:00</td>
<td>15</td>
</tr>
<tr>
<td>2</td>
<td>35</td>
<td>53</td>
<td>7:30-9:00</td>
<td>7:00-10:30</td>
<td>10</td>
</tr>
<tr>
<td>3</td>
<td>15</td>
<td>25</td>
<td>6:00-8:00</td>
<td>5:30-8:30</td>
<td>15</td>
</tr>
<tr>
<td>4</td>
<td>15</td>
<td>50</td>
<td>6:30-8:20</td>
<td>6:00-9:00</td>
<td>15</td>
</tr>
<tr>
<td>5</td>
<td>55</td>
<td>40</td>
<td>6:40-8:30</td>
<td>6:10-10:00</td>
<td>20</td>
</tr>
<tr>
<td>6</td>
<td>45</td>
<td>40</td>
<td>7:00-9:00</td>
<td>6:30-10:20</td>
<td>20</td>
</tr>
<tr>
<td>7</td>
<td>50</td>
<td>20</td>
<td>7:20-9:00</td>
<td>7:00-11:30</td>
<td>20</td>
</tr>
<tr>
<td>8</td>
<td>60</td>
<td>27</td>
<td>7:30-9:00</td>
<td>7:00-10:00</td>
<td>25</td>
</tr>
<tr>
<td>9</td>
<td>40</td>
<td>10</td>
<td>7:00-8:30</td>
<td>6:40-9:30</td>
<td>15</td>
</tr>
<tr>
<td>10</td>
<td>50</td>
<td>5</td>
<td>7:00-9:00</td>
<td>6:30-11:40</td>
<td>10</td>
</tr>
<tr>
<td>11</td>
<td>40</td>
<td>45</td>
<td>7:30-9:30</td>
<td>7:00-12:30</td>
<td>15</td>
</tr>
<tr>
<td>12</td>
<td>55</td>
<td>60</td>
<td>7:30-9:00</td>
<td>7:00-12:00</td>
<td>10</td>
</tr>
<tr>
<td>13</td>
<td>40</td>
<td>65</td>
<td>7:30-9:30</td>
<td>7:00-10:30</td>
<td>10</td>
</tr>
<tr>
<td>14</td>
<td>60</td>
<td>50</td>
<td>7:30-9:00</td>
<td>7:00-11:00</td>
<td>15</td>
</tr>
<tr>
<td>15</td>
<td>65</td>
<td>40</td>
<td>6:50-8:30</td>
<td>7:00-12:00</td>
<td>20</td>
</tr>
<tr>
<td>16</td>
<td>50</td>
<td>30</td>
<td>7:00-8:40</td>
<td>6:20-11:30</td>
<td>25</td>
</tr>
<tr>
<td>17</td>
<td>55</td>
<td>10</td>
<td>7:00-8:40</td>
<td>6:40-11:30</td>
<td>15</td>
</tr>
<tr>
<td>18</td>
<td>25</td>
<td>50</td>
<td>7:50-9:00</td>
<td>7:00-12:00</td>
<td>10</td>
</tr>
<tr>
<td>19</td>
<td>25</td>
<td>60</td>
<td>6:30-8:30</td>
<td>6:00-11:30</td>
<td>25</td>
</tr>
<tr>
<td>20</td>
<td>15</td>
<td>20</td>
<td>7:50-9:00</td>
<td>7:00-11:00</td>
<td>15</td>
</tr>
</tbody>
</table>

4.2 Analysis of experimental result

The proposed algorithm and computations is carried out using MATLABR2017a package; numerical experiments referenced in this paper are evaluated by a computer with windows7-x32 operating system, intel core i7, CPU @ 3.4GHZ and 4GB memory.

4.2.1 Convergence analysis of the algorithm

The section assume the customer satisfaction rate $\alpha$ is 0.95, and $\delta$ equals 0.5. The demand of customer points was processed by Monte Carlo stochastic simulation. For each $G$ value, Monte Carlo sample size $G = [10, 20, 50, 100, 200, 500, 1000]$. Periodic Evolutionary Genetic Algorithm is used to run for 10 times independently. The standard deviation of the objective function is shown in table 3, and it can be seen that the standard deviation of the objective function decreases with the increase of $G$ and tends to stabilize. The results show that the algorithm designed in this paper has good convergence.
Monte Carlo simulation results

<table>
<thead>
<tr>
<th>Monte Carlo simulation times</th>
<th>10</th>
<th>20</th>
<th>50</th>
<th>100</th>
<th>200</th>
<th>500</th>
<th>1000</th>
</tr>
</thead>
<tbody>
<tr>
<td>Standard deviation of objective function</td>
<td>228.8</td>
<td>120.09</td>
<td>93.1</td>
<td>78.1</td>
<td>67.8</td>
<td>26.7</td>
<td>15.6</td>
</tr>
</tbody>
</table>

4.2.2 Sensitivity analysis of the customer satisfaction rate

This section gives the optimal distribution path, corresponding total cost and distribution distance when \( \delta \) equals 0.5 and customers satisfaction rate is 97.5%, 95%, 92.5% and 90% respectively (Fig. 1 and Table 4). It can be concluded that no matter how the customers satisfaction rate changes. The number of vehicles used is always 4. When the customers satisfaction rate is 90%, the minimum total delivery cost and the shortest total delivery mileage are 2797.3 yuan and 394.78 kilometers respectively. When the customers satisfaction rate is 97.5%, the maximum total delivery cost and the longest total delivery mileage are 3618.32 yuan and 536.69 kilometers respectively. With the improvement of customers satisfaction rate. The total cost and total mileage are increasing continuously. Therefore, in the context of customers stochastic demand. Enterprises must make rational planning of vehicle distribution routes in order to meet customer needs.
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Fig. 1. The optimal distribution route under different customers satisfaction rate

The cost detail under deviation is 0.5 and different customers satisfaction rate

| Table 4 |
| --- | --- | --- | --- | --- |
| α value | 97.5% | 95% | 92.5% | 90% |
| Distribution route | 0-4-5-12-19-0 | 0-5-12-2-14-15-11-0 | 0-15-14-12-3-20-0 | 0-19-13-12-14-6-0 |
| | 0-15-10-17-8-0 | 0-9-10-17-6-0 | 0-5-8-10-17-0 | 0-16-7-8-11-0 |
| | 0-16-3-20-9-7-0 | 0-3-19-13-18-4-20-0 | 0-4-19-13-2-18-6-0 | 0-15-5-2-4-18-0 |
| | 0-6-14-1-18-2-13-11-0 | 0-7-1-8-16-0 | 0-16-7-9-1-11-0 | 0-3-20-1-9-10-17-0 |
| Total cost | 3618.32 | 3483.21 | 3052 | 2797.3 |
| Distribution distance | 536.69 | 486.24 | 438.74 | 394.78 |

4.2.3 Sensitivity analysis of maximum deviation value for customers demand

This part analyses the situation when the customer satisfaction rate equals 95% and maximum deviation value is 0, 1, 1.5 and 2 respectively. The number of vehicles required by the optimal distribution path, the total cost and the value of each sub-costs (Table 5). When the maximum deviation value for customers requirement δ is 0, namely the customers demand are deterministic demand. The number of vehicles required is at least 4. The number of vehicles required to meet the customer’s demand is 5, when maximum deviation value is 1, 1.5 and 2 respectively. So the fixed cost is always 1000 yuan, transportation cost, cargo loss cost and refrigeration cost fluctuate less and are relatively stable. Mainly because these cost are affected by transportation distance. The fluctuation of penalty cost and shortage cost are relatively obvious, the penalty cost is determined by the service time window. The shortage cost is determined by the fluctuation of
customers demand. When the customers demand are satisfied at a certain extend. The total cost increases with the increase of maximum deviation value for customers demand. Indicating that the total cost will increase correspondingly if customers demand fluctuate over a large range. The customers demand fluctuate will increase the operating cost of enterprises and reduces the profits of distribution enterprises. Therefore, it is necessary to predict the customers demand of distribution nodes in advance. Reduce the influence of customers demand random fluctuation on the operation cost and customer satisfaction rate of enterprises. Maintain a good relationship between distribution enterprises and customers.

<table>
<thead>
<tr>
<th>Variance value</th>
<th>Number of vehicle</th>
<th>Fixed cost</th>
<th>Transportation cost</th>
<th>Damage cost</th>
<th>Refrigeration cost</th>
<th>Penalty cost</th>
<th>Shortage cost</th>
<th>Total cost</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\delta = 0$</td>
<td>4</td>
<td>800</td>
<td>1195.85</td>
<td>231.37</td>
<td>334.76</td>
<td>115.15</td>
<td>17.9</td>
<td>2695.03</td>
</tr>
<tr>
<td>$\delta = 1$</td>
<td>5</td>
<td>1000</td>
<td>1451.4</td>
<td>213.79</td>
<td>396.84</td>
<td>443.01</td>
<td>249.92</td>
<td>3754.96</td>
</tr>
<tr>
<td>$\delta = 1.5$</td>
<td>5</td>
<td>1000</td>
<td>1807.02</td>
<td>244.33</td>
<td>436.8</td>
<td>517.03</td>
<td>400.86</td>
<td>4406.04</td>
</tr>
<tr>
<td>$\delta = 2$</td>
<td>5</td>
<td>1000</td>
<td>1786.3</td>
<td>268.03</td>
<td>455.53</td>
<td>917.37</td>
<td>712.78</td>
<td>5140.01</td>
</tr>
</tbody>
</table>

5. Conclusion and discussion

In this paper, the chance constrained model of cold chain logistics distribution path with soft time window under stochastic demand is established. The objective function of the model is to minimize the sum of fixed cost, transportation cost, damage cost, refrigeration cost, penalty cost and shortage cost. We have assumed that the demand distribution is unknown, to solve this problem, we design a hybrid algorithm which combines Monte Carlo with periodic evolutionary genetic algorithm. Through practical application cases, the convergence of the algorithm is illustrated. The influence of the change of customer satisfaction rate and customer demand maximum deviation value on the total distribution cost are analyzed. The results show that the model and the algorithm are effective and feasible, which can reflect the impact of customers demand fluctuation and customers satisfaction rate on enterprise distribution cost. Thus, the model and algorithm have certain application value for distribution enterprise path planning. At the same time, the case analysis result pointed out that enterprises must do a good job in the pre-investigation of customers demand. Reducing the impact of random customer demand on the distribution cost of enterprises. Arrange the distribution vehicles reasonably to ensure that the distribution enterprises can maximize the benefits while satisfying customer needs.

Although scholars have done a lot of research on the vehicle routing problem of stochastic demand. There was still few research on cold chain logistics
distribution routing. The cost functions are not comprehensive in the literature [10]. The literature did not take the shortage cost into account. In terms of random demand processing, assumption that the probability distribution of customers demand was known in the literature [10,17,18]. But in fact, customers demand information may show random changes in interval form. Thus, in this paper, the Monte Carlo method was introduced to deal with the chance constraints of stochastic demand. However, this paper also has some shortcomings. For example, a real geographical situations can’t be employed in the distribution path planning. Therefore, the introduction of a road congestion index into the model will be better able to reflect the actual feasible solution in the future research. We are also interested in improving the algorithm with other metaheuristic technique and an iterative process.

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